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ALFRED P. SLOAN SCHOOL OF MANAGEMENT

Forecasting Foreign Exchange Rates Subject to De-volatilization

by

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MIT Sloan School Working Paper 3510
Revised January 16, 1993

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Abstract: There is a considerable literature analyzing the behavior of exchange rates. However, the modeling and forecasting of exchange rates has not been very successful. One of the obstacles to effective modeling of financial time series is heteroscedasticity. The recent availability of high frequency data, such as tick-by-tick data, provides us with extra information about the market. However, even with today's computer power, analyzing data with order of gigabits is extremely expensive and time consuming. This article proposes to analyze a homoscedastic subsequence of such data. The procedure of obtaining such a homoscedastic subsequence is called de-volatilization. The empirical evidence suggests that de-volatilization can help us to detect trends of the market quickly. Our forecasting results indicate that the exchange market can be forecast to certain extend.

Key Words: heteroscedasticity; high frequency data; volatility.

1 Introduction

Empirical studies have shown little success at forecasting foreign exchange rates using structural and time series models (Meese and Rogoff 1983a,b). One of the obstacles to effective modeling and forecasting of exchange rates is conditional heteroscedasticity (changing variance). The ARCH model addresses heteroscedasticity by estimating the conditional variance from historical data and has been used in modeling many financial time series. However, forecasting exchange rates remains difficult. The recent availability of high frequency data has created new possibilities for forecasting exchange rates.

High frequency data, such as minute-by-minute or tick-by-tick data, have recent received attentionly from Goodhart and Figliuoli (1991) and Zhou (1992). As reported in Zhou's paper, high frequency data behave differently from low frequency data and they have significant noise component. Zhou suggested the following process for high frequency exchange rates:

$$S(t) = d(t) + B(\tau(t)) + \epsilon_t \tag{1}$$

where $S(t)$ is logarithm of price at time t, $B(\cdot)$ is standard Brownian motion, $d(\cdot)$ is a drift, $\tau(\cdot)$ is a positive increment function, ϵ_t is a mean zero random noise, independent of Brownian motion $B(\cdot)$. Here $\tau(t)$ is called *cumulate volatility* and increment of $\tau(b) - \tau(a)$ is called *volatility* in period $[a, b]$. The return $X(s, t) = S(t) - S(s)$ then has the following structure:

$$X(s,t) = \mu(s,t) + \sigma(s,t)Z_t + \epsilon_t - \epsilon_s \tag{2}$$

where Z_t is a standard normal random variable and $\sigma(s,t) = \tau(t) - \tau(s)$. Returns of high frequency data are often negatively autocorrelated due to the noises. This autocorrelation decreases as frequency decreases.

This article presents a new approach to heteroscedasticity of financial time series. In Section 2, I introduce a de-volatilization procedure, which takes a homoscedastic subsequence from high frequency data. In Section 3, I test the de-volatilization procedure by examining various properties of de-volatilized exchange rates. Finally, in Section 4, I construct a forecasting procedure from the de-volatilized time series.

2 De-volatilization

One of most significant characteristics of a financial time series is heteroscedasticity. Heteroscedasticity tends to become more severe as sampling frequency increases. This poses a great difficulty in modeling financial time series. One obvious shortcoming of equally spaced time series is that information is insufficient at highly volatile time intervals and is redundant at other times. A time series with more data at highly volatile time and less data at other times is desirable. Unfortunately no financial time series are recorded in this manner. However, availability of high frequency data allows us to sample a subsequence that has equal volatility apart. I call such a procedure *de-volatilization*. The subsequence produced by the procedure is called a de-volatilized time series or *dv-series* and differences of successive measurement of dv-series are called *dv-returns*.

To carry out the de-volatilization procedure, I need to estimate the volatility process $\tau(t)$ first. Given high frequency data, $\{S(t_i)\}$, Zhou (1992) has proposed an estimator of the volatility increment $\tau(b) - \tau(a)$ for any given period $[a, b]$ by:

$$\tau(b) - \tau(a) = \frac{1}{k} \sum_{t_i \in [a,b]} [X^2(t_{i-k}, t_i) + 2X(t_{i-k}, t_i)X(t_{i-2k}, t_{i-k})], \qquad (3)$$

where $X(s,t) = S(t) - S(s)$, and k is a constant. This volatility estimator is nearly unbiased. For a given volatility estimator, I have following de-volatilization procedure:

Algorithm 1 (De-volatilization):
Suppose that $\{S(t_i)\}$ is a series of observations from process (1). This algorithm takes a subsequence from the series and forms a dv-series, denoted as r_τ. The return of the dv-series has approximately the same volatility.

i) Let initial value $r_0 = S(t_0)$;

ii) Suppose that I have obtained an element of dv-series at time t_m, i.e., $r_\tau = S(t_m)$;

iii) Estimate the volatility increment $V(t_{m+i}, t_m) = \tau(t_{m+i}) - \tau(t_m)$ by (3) for $i = 1, \ldots,$ until the increment $V(t_{m+i}, t_m)$ exceeds the level v, a

predetermined constant. Let

$$k = \min\{i; \tau(t_{m+i}) - \tau(t_m) \geq v \text{ and } |S(t_{m+i}) - S(t_{m+i-1})| < \bar{v}\}, \quad (4)$$

$r_{\tau+1} = S(t_{m+k})$ is the next element in dv-series.

iv) Repeat step iii) until end of series $\{S(t_i)\}$.

Since the high frequency exchange rates are characterized by excessive noise, I add an extra condition in (4) to make the dv-series less sensitive to the noise. Often, I see that price jumps back and forth due to noise. When the first jump comes, it may significantly bias the volatility estimate. Waiting for the next data point can minimize the impact of noise on the dv-series.

The de-volatilization procedure is easy to carry out because of the dynamic structure of the volatility estimator. The parameter v can be arbitrarily chosen to meet the different needs of a variety of analyses. However, it should be large enough so that the volatility estimate is acceptable. The noise ratio $\text{Var}(\epsilon_{t_i})/v$ should also be small enough so that the noise ϵ_t in the dv-series can be neglected.

1990 tick-by-tick Deutsche mark and US dollar (DM/\$) exchange rates are used to test our de-volatilization procedure. The same data set has also been used in Zhou (1992). It has more than 2.1 million observations. Yearly volatility is estimated as .010349, and average noise level $\text{Var}(\epsilon) \approx$ 2.6e-8. Based on these figures, I choose v=3e-6. This gives us an average of six hundred data points to estimate the volatility between two dv-series data points, and it is more than one hundred times the noise level. The k in (3) is chosen to be 6 as in Zhou (1992). The basic statistics of the returns of the dv-series are listed in Table 1. The statistics of bi-hourly series are also give in the table for comparison. The variance of dv-return is always a little bit larger than v. Both dv-series and bi-hourly series and their returns are plotted in Figure 1 and 2.

3 Homoscedasticity of Dv-series

Under the assumption that the process (1) is a good approximation of exchange rates, the dv-series should be homoscedastic and dv-returns should be

Figure 1: De-volatilized DM/$ and Its Returns (1990)

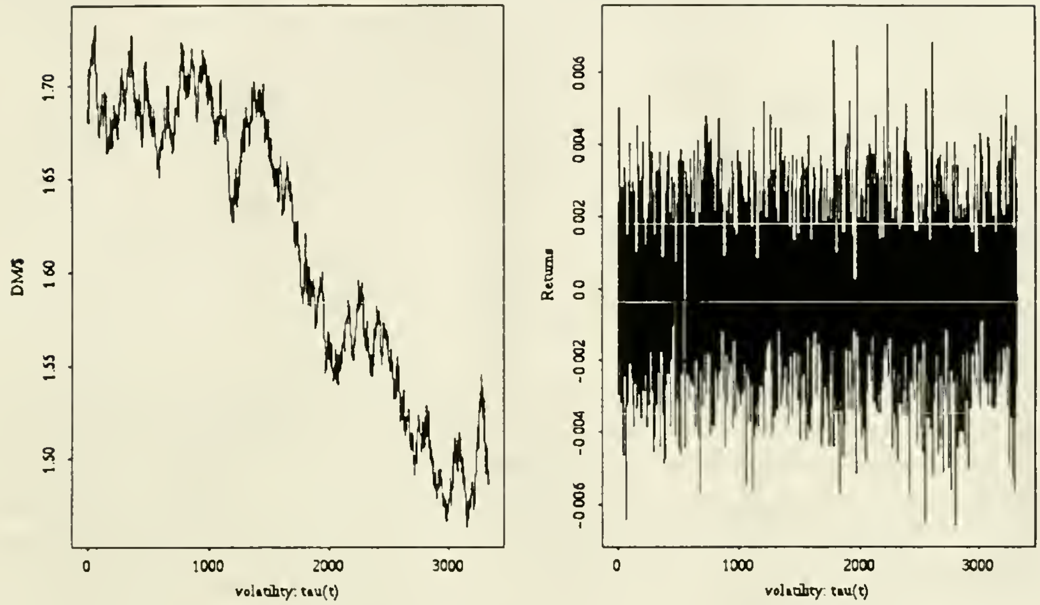


Figure 2: Bi-hourly DM/$ and Its Returns (1990)

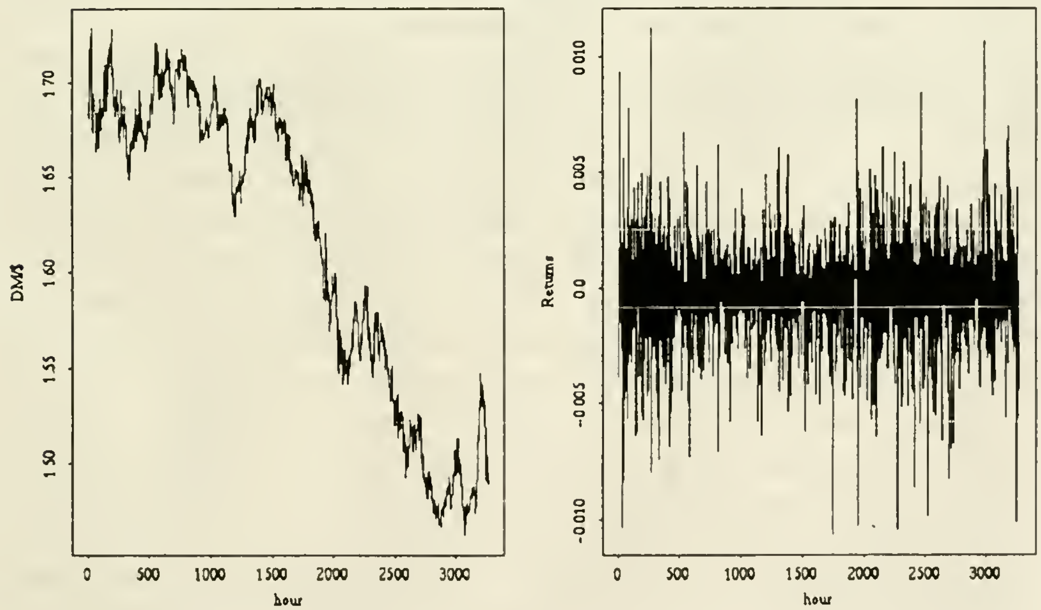


Table 1: Summary Statistics of the Returns: Dv-series and Bi-hourly Seires

	dv-series	bi-hourly
No. Obs.	3324	3268
mean	-3.209e-5	-3.333e-5
Variance	3.578e-6	3.292e-6
Median	0.000	0.000
Skewness	-0.001	-0.394
Kurtosis	2.974	7.809

normally distributed. To visually inspect these properties, I plot month-by-month sample variance and sample kurtosis of dv-returns in Fig. 3. Statistics for bi-hourly returns are also shown for comparison. Fig. 4 shows Q-Q normal plots of both dv-returns and bi-hourly returns. 3 and Q-Q normal plots in Fig. 4. Compared to bi-hourly returns, dv-returns are much closer to homoscedastic; monthly kurtoses are much closer to three and the Q-Q plot is close to a straight line. Therefore I can conclude that the heteroscedasticity of the exchange rate has been largely removed.

To test the normality of dv-returns, I use both the classic Kolmogorov-Smirnov (KS) test and the well-known SW test introduced by Shapiro and Wilk (1965). The SW test statistic is calculated by using a computer program developed by Royston (1982a, 1982b). The test statistics are given in Table 2. The p-value was calculated by computer simulation on 1,000 replications for each sample size. The dv-returns of January and February show marginal significance in the KS test and the dv-returns of June shows marginal significance in the SW test. However, both tests conclusively (at 1% level) reject the normal hypothesis for every month of bi-hourly returns.

When I look at the dv-returns of an entire year, the normality is rejected by the KS test. However, it is not rejected by the SW test, which is considered more powerful than KS test in many cases. The rejection of normality of a series with more than 3,000 observations is not surprising, since no one believes that the return of exchange rate follows exactly normal distribution. De-volatilization only produces an approximately equal volatility apart series.

Figure 3: Monthly Sample Variance and Sample Kurtosis

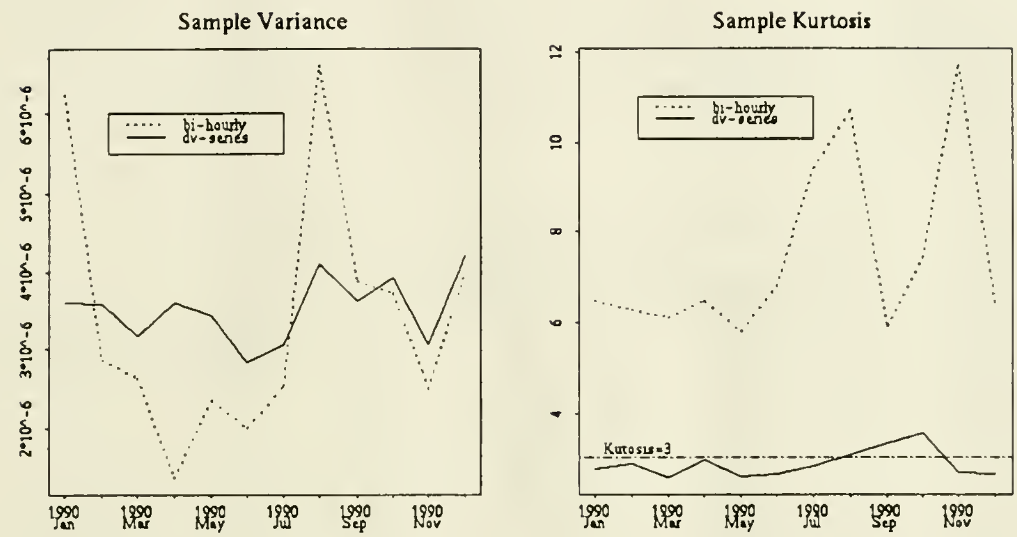


Figure 4: Q-Q normal plots

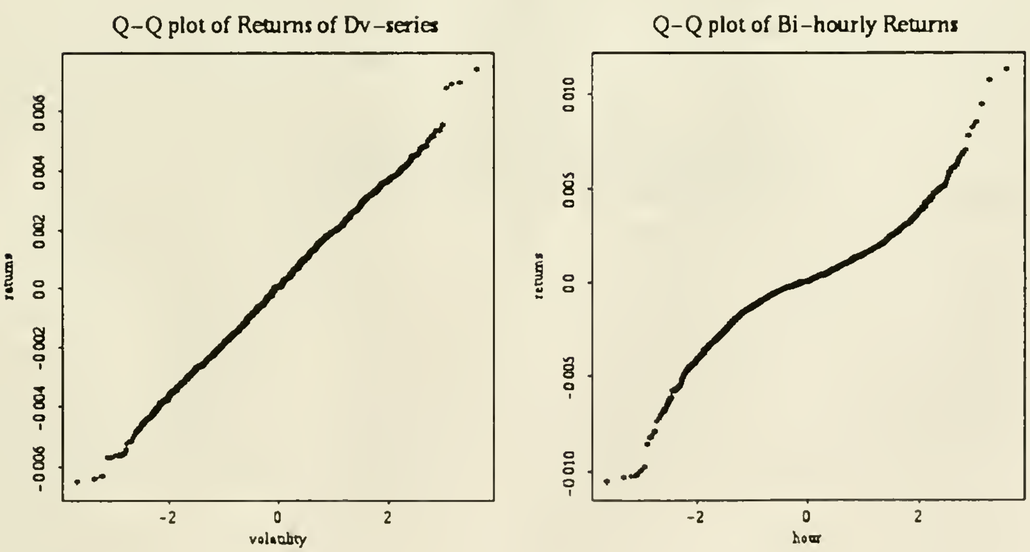


Table 2: Testing Normality of Dv-returns

Month	Size	Kurtosis	KS	SW
Jan.	527	2.741	0.986*	0.985
Feb.	228	2.846	1.033*	0.980
Mar.	232	2.522	0.886	0.979
Apr.	143	2.928	0.544	0.983
May	226	2.559	0.691	0.976
Jun.	161	2.631	0.703	0.967*
Jul.	249	2.792	0.592	0.976
Aug.	371	3.060	0.607	0.987
Sep.	343	3.335	0.877	0.991
Oct.	334	3.543	0.760	0.989
Nov.	245	2.646	0.837	0.981
Dec.	253	2.619	0.731	0.981
1990	3323	2.974	1.422**	0.990

* significant at 5%.

** siginificant at 1%

The normality should be rejected by some tests for a large n. However the test results indicate that normal distribution is not a bad approximation of the distribution of the dv-returns. A small deviation from the normal assumption may indicate that market is not a random walk and that there may be a forecastable component in exchange rates.

To test homoscedasticity, I use the Chi-square test , which can be traced back as early as 1937 (Bartlett 1937; Ostle and Mensing 1975). It is designed to test the null hypothesis of k independent normal populations having the same variance. The test statistic is

$$\chi^2 = 2.3026 \left[\log_{10} s^2 \sum_{i=1}^{k} (n_i - 1) - \sum_{i=1}^{k} (n_i - 1) \log_{10} s_i^2 \right] \tag{5}$$

where s_i^2 and n_i are the sample variance and size of i-th sample and s^2 is the pooled variance defined as:

$$s^2 = \frac{\sum_{i=1}^{k} (n_i - 1) s_i^2}{\sum_{i=1}^{k} (n_i - 1)} \tag{6}$$

Under the assumption that data are normal and the variances are equal for all samples, χ^2 has approximately a chi-square distribution with $k - 1$ degrees of freedom.

Dividing the dv-returns into twelve monthly groups, I have:

$$\chi^2_{dv}(11) = 22.35 \quad (p = 0.022)$$

From the hourly series, which I also divide into twelve monthly subgroups, I have:

$$\chi^2_{hourly}(11) = 273.43 \quad (p = 0.000)$$

Clearly, heteroscedasticity exists in hourly series. However, it is significantly reduced in dv-series.

As do many other financial time series recorded in calendar time, the bi-hourly exchange rate shows autocorrelation in its squared or absolute returns. From our assumption of exchange rates (1), this correlation comes from the autocorrelation of volatilities. Therefore, autocorrelation in its squared returns or its absolute returns should also be removed in dv-returns. The Box-Pierce Q statistic in (7) is chosen to test autocorrelation:

$$Q_m = n \sum_{i=1}^{m} r_i^2 \tag{7}$$

Table 3: Testing Autocorrelation of Dv-series Returns

Q_{10}	X_i	(p)	X_i^2	(p)	$\lvert X_i \rvert$	(p)
dv-series	19.44	(.04)	16.75	(.08)	20.70	(.02)
bi-hourly series	13.68	(.19)	85.14	(.00)	169.42	(.00)

where r_i is sample autocorrelation of time series with lag i, n is size of data. Q_m is approximately $\chi^2(m)$. By choosing $m = 10$, I calculated the Box-Pierce Q statistics for both the dv-returns and the bi-hourly returns. The statistics with their p-values are listed in Table 3. These results show that the autocorrelations of returns, squared and absolute returns for the dv-series are small.

In conclusion, the de-volatilization procedure produced a near homoscedastic dv-series of the exchange rate. The distribution of dv-returns is much closer to a normal distribution than that of bi-hourly returns. These results indicate that forecasting foreign exchange rates is difficult. I do not expect any traditional time series forecast models to be successful here. In the next section, I propose a new forecasting procedure that utilizes the advantages of dv-series.

4 Forecasting Foreign Exchange Rates After De-volatilization

Since the noise ϵ_τ in dv-series is negligible, dv-returns can be written as

$$x_\tau = s_\tau - s_{\tau-1} = \mu_\tau + \sigma Z_\tau,$$

where σ^2 is the variance of the return, μ_τ is the trend (which is often small), and σ^2 is a constant. For 1990 DM/\$ dv-returns obtained in last section, σ^2=3.578e-6. When there is no trend, the return of dv-series ranges from -1.96σ to 1.96σ. However, when the market receives external information, a significant change occurs in drift and the return is likely out of -1.96σ to 1.96σ band. I say that an "event" has occurred whenever a dv-return falls

Table 4: Correlation of Price Changes During and After the "Events"

k	r_k	k	r_k	k	r_k	k	r_k
1	-0.028	6	0.165*	11	0.148	16	0.097
2	0.039	7	0.134	12	0.125	17	0.056
3	0.119	8	0.178*	13	0.111	18	0.049
4	0.182*	9	0.144	14	0.126	19	0.032
5	0.180*	10	0.150	15	0.084	20	0.016

* indicates significant at 5% level.

outside this -1.96σ to 1.96σ band. If the market is not pure random walk, a trend may be formed after the event. To test this hypothesis, I calculate the correlation between the price changes during the event and the ones after the event. Let E be the index set of all events,

$$E = \{\tau, |x_\tau| > 1.96\sigma\}$$

Correlation coefficients

$$r_k = \frac{\sum_{\tau \in E} x_\tau (x_{\tau+1} + \ldots + x_{\tau+k})}{(\sum_{\tau \in E} x_\tau^2 \sum_{\tau \in E} (x_{\tau+1} + \ldots + x_{\tau+k})^2)^{1/2}}$$

are calculated and listed in Table 4. There are total 147 "events" in 1990.

By examining Table 4, I find that there is a positive correlation between the initial movement of the price during the event and the trend after the events. The trend lasts only several steps. Therefore it is difficult to analyze using daily data. To further test exchange rates' forecastability, I propose a simple forecasting procedure:

Algorithm 2 (Forecasting procedure I) Given a dv-series $\{s_\tau, \tau = 0, \ldots, n\}$, this procedure generates forecasting signals $\delta_\tau \in \{-1, 0, 1\}$ corresponding to downward, flat and upward trends.

- Initialize all δ_τ to 0, $\tau = 1, \ldots, n$;

- If $|s_\tau - s_{\tau-1}| > 1.96\sigma$

$$\delta_{\tau+i} = \text{sign}(s_\tau - s_{\tau-1}), \quad i = 1, ...k, \text{ and } \tau + i < n;$$

  This forecast overwrites any previous forecast.

To evaluate the forecast, I use following criteria:

$$CI = \sum \delta_\tau \text{sign}(x_\tau) \tag{8}$$
$$CII = \sum \delta_\tau x_\tau \tag{9}$$

CI is the difference between the number of right and wrong predictions and CII is total return assuming no transaction costs. The larger they are the better. If dv-returns are independent mean zero random noises, the forecast signal δ_τ depends only on returns x_i, $i < \tau$ and both CI and CII have approximately normal distribution with

$$\mathbf{E}[CI] = 0 \quad \text{and} \quad \text{Var}(CI) = np,$$

and

$$\mathbf{E}[CII] = 0 \quad \text{and} \quad \text{Var}(CII) = np\sigma^2.$$

where n is the number of non-zero returns and p is the percentage of non-zero forecast signals among these returns.

The only parameter in the procedure is the integer k, the length of the trend. The σ is predetemined by the de-volatilization procedure and is not to be estimated in this procedure. Table 4 suggests that k lie in the interval 3 to 14. To illustrate, I list forecasting results of 1990 DM/\$ for all $k = 1, .., 15$ in Table 5. When $k = 5$, both CI and CII are significantly greater than zero at the 5% level.

Although this is a nonparametric procedure, it is analyzed using the 1990 data retrospectively. It is more convincing to forecast a succeeding year of exchange rates. I obtained 1991 DM/\$ tick-by-tick data from J.P. Morgan. Using exactly the same de-volatilization procedure and forecasting procedure, I show forecast results of 1991 DM/\$ in Table 6. For 1991, CI and CII are not only significant at $k = 5$, but at many other choices of k as well.

I conclude that the exchange rate often forms a trend after the "event" and this trend is forecastable. The forecasting result is very encouraging.

Table 5: Forecasting 1990 DM/$ by Forecasting Procedure I

k	CI	CI/SE	CII	CII/SE	np
1	0	0.00	-0.018	-0.83	132
2	13	0.80	0.012	0.40	265
3	40	2.02	0.048	1.28	392
4	58	2.56	0.084	1.95	514
5	65	2.58	0.105	2.20	635
6	48	1.75	0.068	1.32	750
7	47	1.61	0.056	1.01	857
8	48	1.55	0.079	1.34	962
9	48	1.47	0.071	1.15	1062
10	53	1.56	0.089	1.38	1161
11	66	1.86	0.108	1.61	1256
12	80	2.18	0.110	1.59	1344
13	69	1.83	0.090	1.26	1427
14	64	1.65	0.095	1.30	1508
15	51	1.28	0.074	0.99	1589

Table 6: Forecasting 1991 DM/$ by Forecasting Procedure I

k	CI	CI/SE	CII	CII/SE	np
1	21	1.39	0.029	1.01	229
2	39	1.85	0.067	1.68	445
3	30	1.18	0.049	1.02	648
4	54	1.87	0.098	1.79	834
5	54	1.70	0.135	2.25	1012
6	70	2.04	0.166	2.56	1180
7	66	1.81	0.180	2.61	1336
8	61	1.58	0.170	2.33	1489
9	65	1.61	0.190	2.48	1633
10	65	1.54	0.175	2.20	1773
11	66	1.51	0.171	2.07	1906
12	54	1.20	0.157	1.84	2028
13	56	1.21	0.160	1.83	2136
14	82	1.73	0.240	2.68	2240
15	76	1.57	0.247	2.70	2340

However profits are very slim if I take account of the bid-offer spread. Using the following simple trading program with $k = 5$ and bid offer spread .05% of the price, I have profit=2.1% for 1990 and profit=2.6% for 1991. Further improvement is necessary to make the forecast more profitable.

Algorithm 3 (Trading Program) This program assumes that a fixed number of US dollars are traded at each position.

- At time τ, suppose that no position is held.
  1. If $\delta_{\tau+1}=1$, take a long position;
  2. If $\delta_{\tau+1} = -1$, take a short position;
- At time τ, suppose that one position is held,
  1. If $\delta_{\tau+1}\delta_\tau > 0$, keep the same position;
  2. If $\delta_{\tau+1}\delta_\tau = 0$, terminate the position;
  3. If $\delta_{\tau+1}\delta_\tau < 0$, reverse the position;
- If one position bought at time τ_0 and sold at time τ_1,

$$\text{profit} = [\frac{\delta_{\tau_0}(\exp(s_{\tau_1}) - \exp(s_{\tau_0}))}{\exp(s_{\tau_0})} - .0005] \times 100\%. \qquad (10)$$

Recent stock market studies suggest that price has less autocorrelation during period of large volume or large volatility (LeBaron 1990, Campbell, etc., 1992). If this is also true for currency exchange markets, an event occuring during a period of extremely high volatility may not form a future trend. I therefore modify our forecasting procedure as follows:

Algorithm 4 (Forecasting procedure II) Given a dv-series $\{s_\tau,\ \tau = 0, ..., n\}$, this procedure generates forecasting signals $\delta_\tau \in \{-1, 0, 1\}$ corresponding to downward, flat and upward trends. Let $t(\tau)$ be the time (in second) that price s_τ is recorded and $\bar{v}_{hr}$ be average hourly volatility,

- Initialize all δ_τ to 0, $\tau = 1, ..., n$;
- If $|s_\tau - s_{\tau-1}| > 1.96\sigma$, and
  1. if $\sigma^2/[t(\tau) - t(\tau-1)] < \alpha\bar{v}_{hr}/3600$,

$$\delta_{\tau+i} = \text{sign}(s_\tau - s_{\tau-1}), \quad i = 1, ...k, \text{ and } \tau + i < n;$$

2. if $\sigma^2/[t(\tau)-t(\tau-1)] \geq \alpha\bar{v}_{hr}/3600$, set all nonzero $\delta_{\tau+i}$, $i>0$, to be zero;

This forecast overwrites any previous forecast.

Empirical results show that forecast procedure II increases not only the values of CI and CII, but the profitability as well. The results of forecasting with $\alpha = 5$ are listed in Table 7 and 8. The choice of $\alpha = 5$ in the forecasting procedure is arbitrary. Results for α between 4 and 6 are very similar. For $4 \leq k \leq 11$, CI and CII for both 1990 and 1991 are significant at the 5% level. Both years show sizeable profits. For $k = 10$, there is 9.03% profit in 1990 with only 26.7% of total time in the market and 18.62% profit in 1991 with only 25.5% of total time in the market. In Figure 5 and 6, I show: (a) dv-series; (b) forecast signal δ_τ and (c) cumulate profit/loss curve.

There is another interesting result: most profits are from "events" that happened in European and the US markets. The "events" in other markets are merely noises. Dividing the 24-hour market into four sections: Europe only (3:00am EST/EDT - 8:00am EST/EDT), Europe and US (8:00am EST/EDT - 12:00pm EST/EDT), US only (12:00pm EST/EDT - 5:00pm EST/EDT) and Asia/other (5:00pm EST/EDT - 3:00am EST/EDT next day), I calculate possible profits from the "events" in different section of the market (Table 9). The numbers may not add up to the total in Table 7 and 8 because that a position taken in one section may hold into next section of the market.

The largest number of "events" occur during the period that both European an American markets are open, although this section of the market only lasts four hours. Profit distribution in different sections of the market is consistent with our expectation that only news from European or US markets is relevant to the DM/$ exchange rates. These results indicate the correlation between the "events" in my forecasting procedure and real news events in the market.

5 Discussion

I believe that foreign exchange markets do not follow a pure random walk. It is consisted with many small trends. These trends last only a day or two

Table 7: Forecasting 1990 DM/$ by Forecasting Procedure II

k	CI	CI/SE	CII	CII/SE	profit	P.P.-L.P.	P.T./T.T
1	6	0.59	0.001	0.04	-5.57%	54-48	1.8%
2	16	1.11	0.028	1.03	-2.75%	59-48	4.8%
3	41	2.34	0.069	2.09	1.51%	59-43	7.1%
4	55	2.73	0.099	2.59	4.51%	68-37	9.8%
5	72	3.21	0.141	3.32	8.86%	65-37	12.8%
6	61	2.49	0.117	2.53	6.52%	62-39	16.1%
7	63	2.40	0.117	2.37	6.64%	58-41	19.6%
8	64	2.30	0.134	2.55	8.44%	58-37	22.0%
9	64	2.18	0.125	2.26	7.56%	56-42	24.2%
10	67	2.18	0.139	2.39	9.03%	55-40	26.7%
11	68	2.13	0.142	2.35	9.49%	55-37	28.7%
12	82	2.47	0.143	2.29	9.69%	54-38	31.1%
13	73	2.13	0.129	2.00	8.38%	51-38	33.5%
14	71	2.02	0.136	2.04	9.09%	53-36	35.5%
15	58	1.60	0.117	1.71	7.27%	48-40	37.9%

P.P.-L.P.: profit postions - loss positions

P.T./T.T.: postion time / total time of the year $\times$ 100%

Table 8: Forecasting 1991 DM/$ by Forecasting Procedure II

k	CI	CI/SE	CII	CII/SE	profit	P.P.-L.P.	P.T./T.T
1	20	1.70	0.025	1.12	-4.76%	78-57	1.6%
2	40	2.43	0.073	2.33	0.33%	79-57	4.4%
3	33	1.66	0.073	1.92	0.52%	74-53	6.2%
4	62	2.73	0.121	2.81	5.53%	73-55	7.8%
5	76	3.02	0.173	3.62	10.82%	79-48	13.2%
6	85	3.10	0.194	3.74	13.07%	80-45	15.5%
7	90	3.07	0.226	4.06	16.34%	78-46	18.3%
8	93	2.98	0.238	4.04	17.63%	82-41	20.6%
9	96	2.93	0.260	4.20	19.98%	73-46	22.7%
10	89	2.59	0.245	3.77	18.62%	73-46	25.5%
11	84	2.35	0.223	3.30	16.48%	72-44	28.6%
12	64	1.73	0.179	2.56	12.17%	69-47	31.4%
13	67	1.75	0.198	2.73	14.03%	68-46	33.3%
14	67	1.70	0.219	2.93	16.29%	69-42	34.5%
15	73	1.80	0.236	3.08	18.25%	62-47	36.3%

P.P.-L.P.: profit postions - loss positions
P.T./T.T.: postion time / total time of the year × 100%

Table 9: Distribution of Events and Profits in Different Sections of the Market ($k = 10$)

Year		Europe Only 3am-8am EST/EDT	Europe & US 8am-12am EST/EDT	US Only 12am-5pm EST/EDT	Asia/Other 5pm-3am EST/EDT
	P.P.–L.P.	8–10	24–10	15–9	20–13
1990	Profit	–2.21%	7.80%	4.84%	1.01%
	P.P.–L.P.	26–16	29–18	13–10	15–13
1991	Profit	7.98%	8.38%	1.53%	–0.97%

Figure 5: Forecast 1990 DM/$ by Procedure II ($k = 10$)

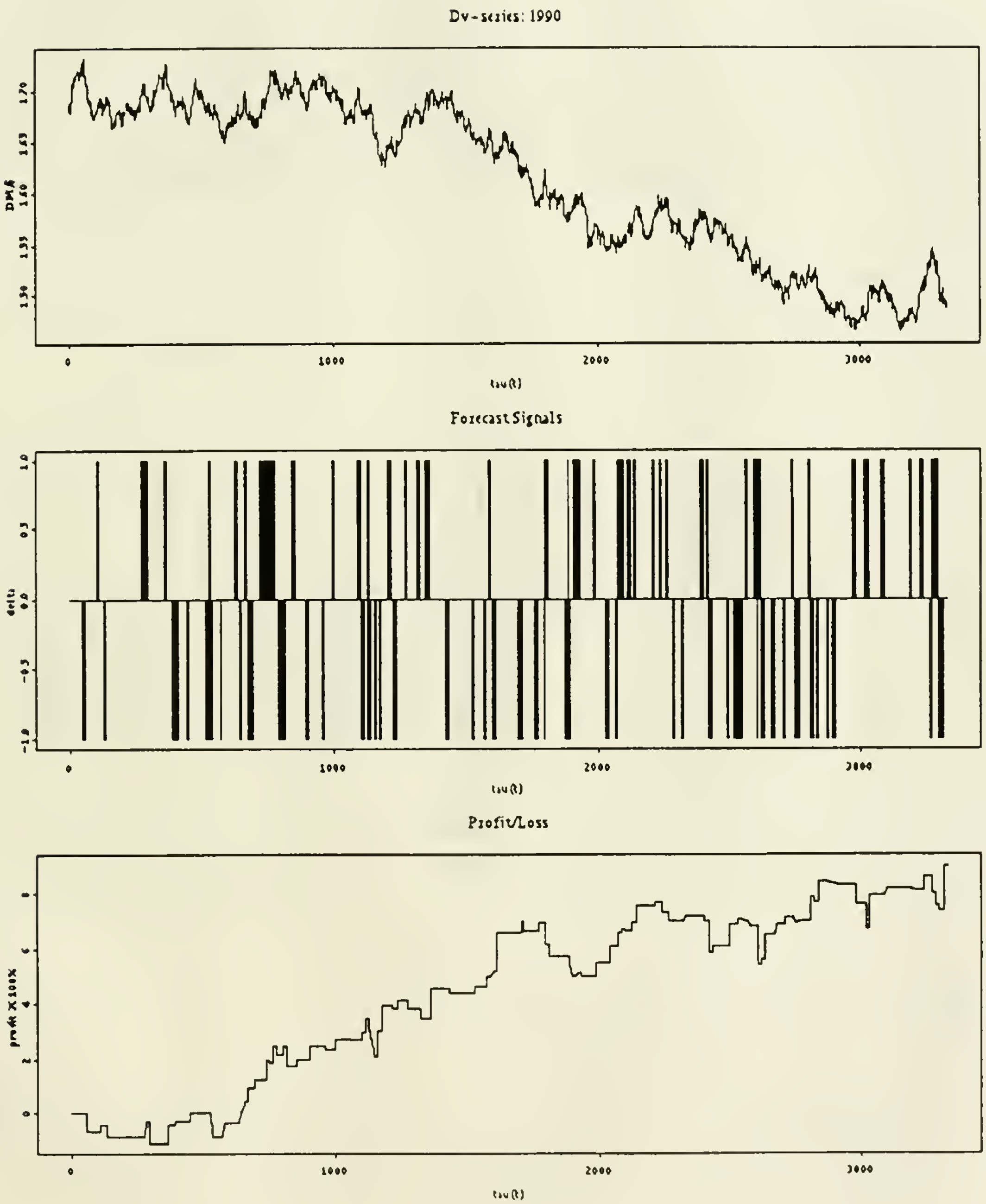
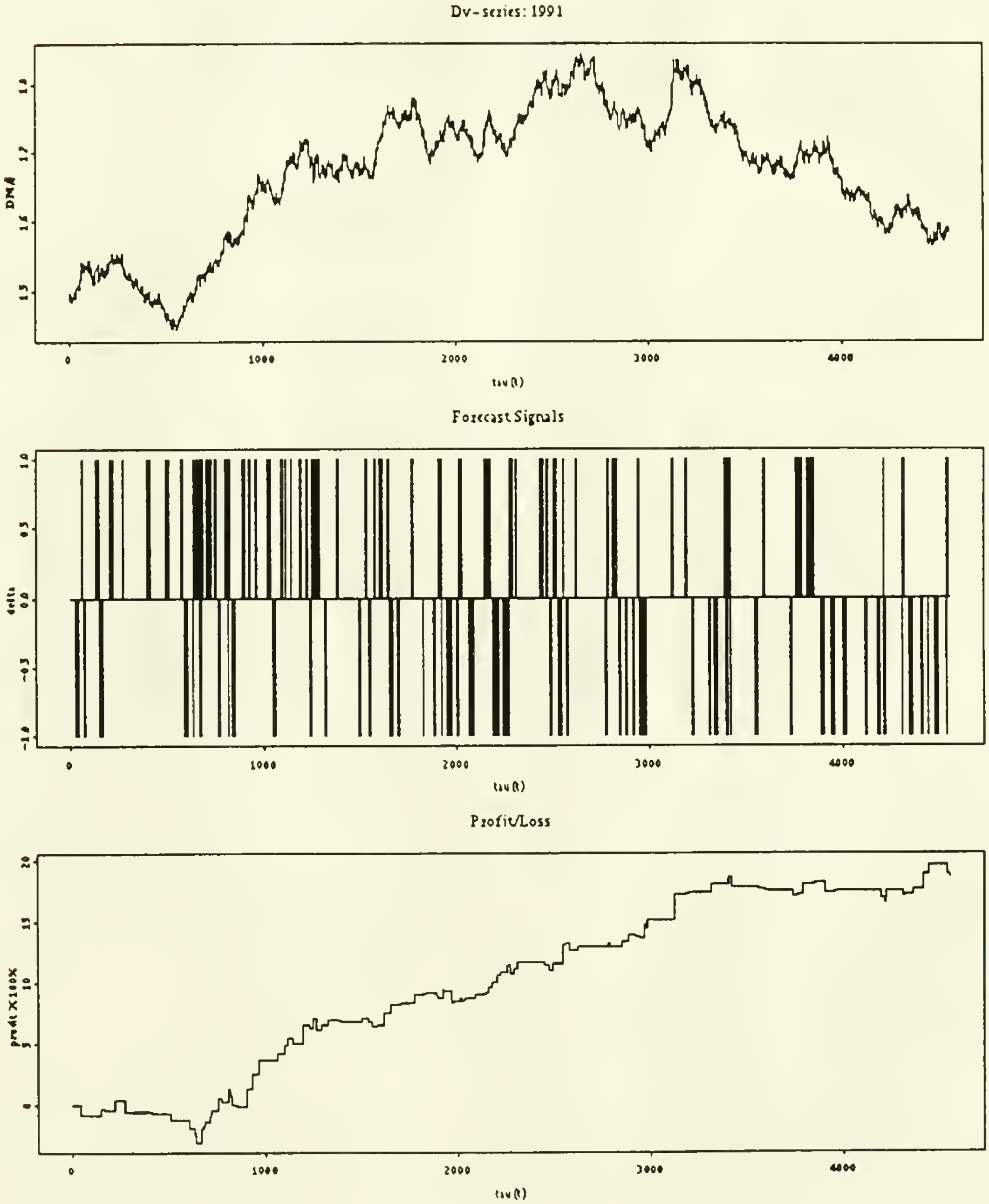


Figure 6: Forecast 1991 DM/$ by Procedure II ($k = 10$)



and occur in random directions. Consequently precise forecasting of daily exchange rates is extremely difficult.

De-volatilization is an efficient way to use high frequency data. It not only reduces the noise effect in the data, but reduces heteroscedasticity as well. The de-volatilization procedure takes more observations in an active market and helps to detect trends early. It corresponde closely to the way sophiscaticated traders "look" at exchange markets. The procedure can be used in any market with high frequency observations.

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